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IMPROVEMENT OF POWER SYSTEM PERFORMANCE THROUGH WAVELET NEURAL NETWORK STATIC VAR COMPENSATOR CONTROLLER

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ABSTRACT– *This paper aimed to apply a nonlinear hybrid wavelet neural network, WNN controller for static VAR compensators SVC. The proposed WNN control the amount of the reactive power consumed or delivered to the network by controlling the TRC firing angle. Single layer wavelet neural network, WNN model technique is used in the present paper. The proposed controller tracks the power systems response to zero error in the post fault conditions. The proposed controller is applied for sample single machine infinite bus power system. The time simulations indicate the effectiveness, robustness and fast response of the proposed controller in comparison with the conventional one's. The studied system is modeled by nonlinear differential and algebraic equations which solved by the Matlab Software.*

KEYWORDS: *Static VAR Compensators – FACTS - Wavelet neural network – Power system stability.*

1. INTRODUCTION

The SVC is one of the most important FACTS devices which are very effective for voltage regulations and stability improvement of the power systems. Due to the extensions of the power networks the use of SVC became very essential.

Fixed capacitors, Thyristor control reactors static VAr Compensators SVC are used world wide for utilities purposes. The main objective of inserting such SVC systems is to regulate the node voltages at weak points of the utility grid as well as maintaining the voltage stability of industrial loads[1-6]. However it is also can be used for improving the power system dynamic performance in case of abnormal operating conditions[7-8].

The control system is usually designed based on linearizing the system model around a prescribed operating conditions. The linear regulator theory, direct feed back linearization and exact linearization are usually used. Stabilization process based on these conventional linear control theory with fixed parameters are working very well, and provide a very good damping in a prescribed operating conditions. Such intelligent control techniques has been recently introduced, to be used in power systems such as adaptive neural network, ANN, fuzzy logic FL control, adaptive neuro Fuzzy, expert system, genetic algorithms[9-14]. The advantages of these control techniques provide a very effective damping than the conventional control theory, with better control quality and independent of power systems parameters.

The present paper introduces wavelet neural network, WNN controller for static VAR Compensator, which train the data online and independent of the system parameters. The damping effect of the proposed WNN is evaluated in a comparative study with conventional PI controller. The Comparative Study proves the superiority of the proposed controller over the conventional one's with better control quality.

2. STUDIED SYSTEM FOR FEASIBILITY STUDY

The studied power system is shown in **Fig. 1**. The system data is given in [7].

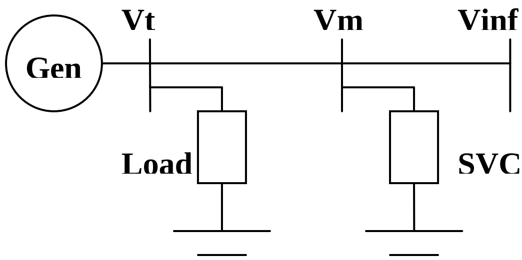

Fig. 1: Studied Power System With SVC.

3. STUDIED SYSTEM MODELING

3.1. Generator Model

A Two-Axis dynamic model [15] has been used in this study. The system dynamic Equations are given by:

$$\dot{\delta} = \omega - \omega_s \tag{1}$$

$$M\dot{\omega} = T_M - [E_q^{\backslash} - X_d^{\backslash} i_d] i_q - [E_d^{\backslash} - X_q^{\backslash} i_q] i_d - D(\omega - \omega_s) \tag{2}$$

$$T_{do}^{\backslash} \dot{E}_q^{\backslash} = -E_q^{\backslash} - (X_d - X_d^{\backslash}) i_d + E_{fd} \tag{3}$$

$$T_{qo}^{\backslash} \dot{E}_d^{\backslash} = -E_d^{\backslash} - (X_q - X_q^{\backslash}) i_q \tag{4}$$

3.2. Exciter Model

In this study, The IEEE Type DC-1 Exciter [15] has been used. The dynamic equations for this exciter are given by:

$$T_E \dot{E}_{fd} = -(K_E + S_E(E_{fd}))E_{fd} + V_R \tag{5}$$

$$T_A \dot{V}_R = -V_R + K_A R_f - \frac{K_A K_f}{T_f} E_{fd} + K_A(V_{ref} - V_t) \tag{6}$$

$$T_F \dot{R}_f = -R_f + \frac{K_f}{T_f} E_{fd} \tag{7}$$

3.3. Static VAR Model

The static Var compensator has many different models presented by literatures [5]. In this paper the used SVC is consisted of Fixed Capacitor and Thyristor Controlled reactor, (FC-TCR) Type. The firing angle α of the reactor thyristor can be controlled using the proposed controller. It's currents are related to the firing angles by the following equations:

$$I_L(\alpha) = \frac{V(2\pi - 2\alpha + \sin 2\alpha)}{\pi\omega L} \tag{8}$$

where $\pi/2 \le \alpha \le \pi$

$$I_L(\sigma) = \frac{V(\sigma - \sin\sigma)}{\pi\omega L} \tag{9}$$

From the above equation the reactor virtual susceptance can be expressed as:

$$B_L(\sigma) = \frac{I_L(\sigma)}{V} \tag{10}$$

from equations (9) and (10) the susceptance can be expressed as:

$$B_L(\sigma) = \frac{\sigma - \sin\sigma}{\pi\omega L} \tag{11}$$

The overall SVC susceptance is given by the summation of the fixed capacitor susceptance and the thyristor controlled variable reactor susceptance, which expressed as:

$$B_{SVC} = B_c + B_L(\sigma) \tag{12}$$

4. WAVELET NEURAL NETWORK CONTROLLER PRINCIPLES

The present wavelet neural network, WNN controller which consists of four layer controller is discussed in [16]. The target of the controller is to track the speed deviations, and torque angle deviation to zero, in case of severe disturbance. To develop this controllers, two input error signals were selected, the first one is the speed deviation, which is taken as a tracking error, ε_1 and it's rate of change. The input of the

WNN controller consists of the errors ε_1, $\varepsilon_1(1\text{-}z^{-1})$ with z^{-1} is the time delay. The output of the WNN will be added to the voltage regulator gain to form the angle α.

4.1. WNN Technique Analysis

The signal propagation and the basic function in each ANN layer can be displayed in the following. For every node *i* in the input layer, the net input and the net output can be described by the following equations:

$$net_i^1 = x_i^1 \quad y_i^1 = f_i^1(net_i^1) = net_i^1, \quad i = 1,2 \tag{13}$$

where $x_1^1 = \varepsilon$ and $x_2^1 = \varepsilon(1 - z^{-1})$

The family of the wavelet is usually constructed by translation and dilations performed on a single fixed function, called the mother wavelet. In which layer, each node performs a wavelet Φ_j that is derived from its "mother wavelet". The first derivative of a Gaussian function, is adopted as a mother wavelet in this study, and expressed as $\Phi(x) = -x\exp(-x^2/2)$. For the jth node

$$net_j^2 = (x_i^2 - m_{ij})/\sigma_{ij} \tag{14}$$

$$y_j^2 = f_j^2(net_j^2) = \phi_j(net_j^2) \quad j = 1,\ldots,n \tag{15}$$

Where m_{ij} and σ_{ij} are the translation and dilation in the jth term of the ith input x_i^2 to the node of mother wavelet layer, and n is the all number of wavelets with respect to the input nodes. Each node k in the wavelet layer is denoted by Π, which multiplies in the input signals and outputs result of the product[14]. Hence, for the kth rule node

$$net_k^3 = \prod_j w_{jk}^3 x_j^3, \quad y_k^3 = f_k^3(net_k^3) = net_k^3, \quad k = 1,\ldots,l \tag{16}$$

Where x_j^3 represents the jth input to the node of the wavelet layer, and w_{jk}^3 is the weights between the mother wavelet layer and the wavelet layer, and assumed to be unity. The number of the wavelet is given as l=n/i if each input node has the same mother wavelet nodes. The Σ is known as the single node 0 in the output layer, which compute the overall output as the summation of all input signals.

$$net_o^4 = \sum_k k_{ko}^4 x_k^4 \quad y_o^4 = f_o^4(net_o^4) = net_o^4, \; o = 1 \tag{17}$$

Where the connecting weight w_{ko}^4 is the output action strength of the Oth output associated with the kth wavelet, and x_k^4 represents the kth input to the node of output layer,

and $y_1^4 = \alpha$. (18)

Hence the output signal of the controller is as given in the above equation.

4.2. On-line Training Algorithm for Wavelet Neural network

The main part of the training algorithm is how to obtain a gradient vector in which each element in the training algorithm is defined as the derivative of the energy function with respect to the parameters of the network. This can be obtained by the chain rules, and the method is generally referred to as back propagation learning rules. In order to illustrate the on-line training mechanism of the WNN using the supervised gradient descent method, the energy function should firstly defined as $E=0.5\ e^2$. Hence, the on-line training mechanism, based on back propagation can be expressed as follows:

$$\delta_o^4 = -\frac{\partial E}{\partial y_o^4} = \left[-\frac{\partial E}{\partial \varepsilon}\frac{\partial \varepsilon}{\partial y_o^4} \right] \tag{19}$$

The weight ΔW_{ko}^4 can be updated by the equation

$$\Delta w_{ko}^4 = -\eta_w \frac{\partial E}{\partial w_{ko}^4} = \left[-\eta_w \frac{\partial E}{\partial y_o^4} \right]\left[\frac{\partial y_o^4}{\partial net_o^4}\frac{\partial net_o^4}{\partial w_{ko}^4} \right] = \eta_w \delta_o^4 x_k^4 \tag{20}$$

The weights of the layers are updated according to the following equation:

$$w_{ko}^4 (N+1) = w_{ko}^4 (N) + \Delta w_{ko}^4 \tag{21}$$

Where N is the iteration number and η_w is the weight learning rate.

The weights in the wavelet layer are unity, hence the error term needs to be calculated and propagated. The error term is then

$$\delta_k^3 = -\frac{\partial E}{\partial net_k^3}\left(-\frac{\partial E}{\partial y_o^4} \right)\left(\frac{\partial y_o^4}{\partial net_o^4}\frac{\partial net_o^4}{\partial y_k^3}\frac{\partial y_k^3}{\partial net_k^3} \right) = \delta_o^4 w_{ko}^4 \tag{22}$$

The error term can be obtained by the following equation

$$\begin{aligned}\delta_j^2 &= -\frac{\partial E}{\partial net_j^2} \\ &= \left(-\frac{\partial E}{\partial y_o^4}\frac{\partial y_o^4}{\partial net_o^4}\frac{\partial net_o^4}{\partial y_k^3}\frac{\partial y_k^3}{\partial net_k^3} \right)\left(\frac{\partial net_k^3}{\partial y_j^2}\frac{\partial y_j^2}{\partial net_j^2} \right) \\ &= \sum_k \delta_k^3 y_k^3 \end{aligned} \tag{23}$$

The update rule of m_{ij} is as follows:

$$\Delta m_{ij} = -\eta_m \frac{\partial E}{\partial m_{ij}} = \left(-\eta_m \frac{\partial E}{\partial y_j^2}\frac{\partial y_j^2}{\partial net_j^2}\frac{\partial net_j^2}{\partial m_{ij}} \right) = -\eta_m \frac{\delta_j^2}{\sigma_{ij}} \tag{24}$$

The rule for updating σ_{ij} is as follows:

$$\Delta\sigma_{ij} = -\eta_\sigma \frac{\partial E}{\partial \sigma_{ij}} = \left(-\eta_\sigma \frac{\partial E}{\partial y_j^2} \frac{\partial y_j^2}{\partial net_j^2} \frac{\partial net_j^2}{\partial \sigma_{ij}} \right)$$

$$= -\eta_\sigma \delta_j^2 \frac{(m_{ij} - x_i^2)}{(\sigma_{ij})^2} \tag{25}$$

The dilation and translation of the mother wavelet can be updated as follows:

$$m_{ij}(N+1) = m_{ij}(N) + \Delta m_{ij} \tag{26}$$

$$\sigma_{ij}(N+1) = \sigma_{ij}(N) + \Delta\sigma_{ij} \tag{27}$$

Where η_σ and η_m are the learning rates of the dilation and translation of the mother wavelet. To increase the on-line learning rate of the weights, the following approximation rule is adopted:

$$\delta_o^4 \cong \varepsilon + \varepsilon(1 - z^{-1}) \tag{28}$$

The values of the learning rates affect the network performance. In order to train the WNN effectively, adaptive learning rates, which assure the convergence of tracking error based on the analysis of a discrete type Lyapunov function. The convergence analysis in this study is to derive a specific learning rates for specific types of network parameters to assure convergence of the tracking error[20].

Assume η_w be the learning rate of the WNN weights and

$P_{w\,max} = \max_N \| P_W(N) \|$ with, $P_W(N) = \partial y_o^4 / \partial w_{ko}^4$ and $\| . \|$ is the education norm in R^n. The convergence is guaranteed if η_w is chosen as $\eta_w = \lambda / P_{w\,max}^2 = \lambda / R_u$, in which λ is a positive constant gain, and R_u is the number of nodes in the wavelet layer of the WNN.

Since $P_W(N) = \partial y_o^4 / \partial w_{ko}^4 = x_k^4$, Then $\| P_W(N) \| < \sqrt{R_u}$. The discrete type lyapunov function is selected as: $V(N) = e^2(N)/2$. The change in the lyapunov function is obtained by $\Delta V(N) = V(N+1) - V(N) = [e^2(N+1) - e^2(N)]/2$ Therefore, error difference can be expressed as:

$$e(N+1) = e(N) + \Delta e(N) = e(N) + \left[\frac{\partial e(N)}{\partial w_{ko}^4} \right]^T \Delta w_{ko}^4 \tag{29}$$

Where $\Delta\, w_{ko}^4$ represents a weight change in the output layer. Using Eqns. (19),(20) and (30) Then,

$$\frac{\partial e(N)}{\partial w_{ko}^4} = \frac{\partial e(N)}{\partial y_o^4} \frac{\partial y_o^4}{\partial w_{ko}^4} = -\frac{\delta_o^4}{e(N)} P_w(N) \tag{30}$$

and

$$e(N+1) = e(N) - \left[\frac{\delta_o^4}{e(N)} P_w(N) \right]^T \eta_w \delta_o^4 P_w(N) \tag{31}$$

Hence

$$P_W(N) = \partial y_o^4 / \partial w_{ko}^4 = x_k^4, \tag{32}$$

Thus

$$\|e(N+1)\| = \| e(N)[1-\eta_w [\delta_o^4 / e(N)]^2 P_w^T(N) P_w(N)] \|$$
$$\leq \|e(N)\| \| 1-\eta_w [\delta_o^4 / e(N)]^2 P_w^T(N) P_w(N) \| \tag{33}$$

If η_w is chosen as $\eta_w = \lambda / P_{w\ max}^2 = \lambda / R_u$, The term $\|1- \eta_w [\delta_o^4 / e(N)]^2 P_w^T(N) P_w(N)\|$ in the above Eq. Is less than 1. Therefore, the Lyapunov stability of $\Delta V > 0$ and $\Delta V < 0$ is guaranteed. The tracking error will converge to zero when $t \rightarrow \infty$.

5. DESIGN OF WNN STATIC VAR COMPENSATOR CONTROLLER

The present WNN static Var compensator controller implements two input signals the speed deviation and rate of change of speed deviations. The output wavelet neural network static Var compensator controller signal is α. The schematic diagram of such WNN static Var compensator controller is given in **Fig. 2**.

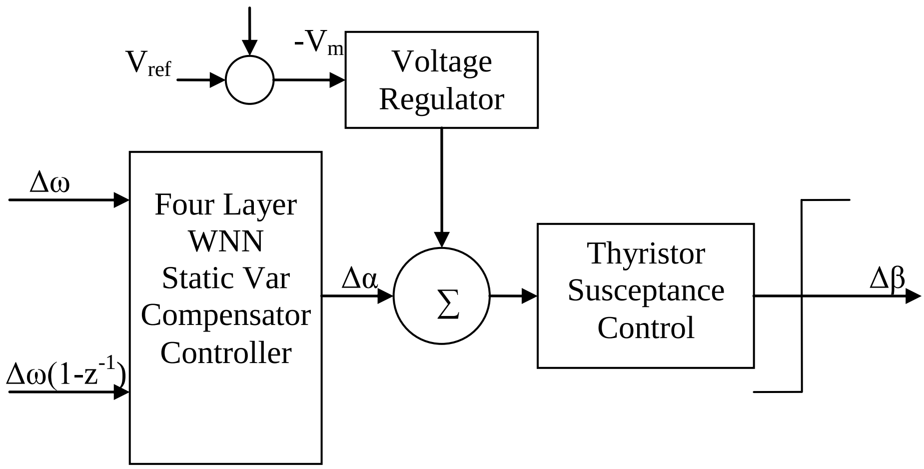

Fig. 2: Schematic diagram for the proposed WNN Static Var Compensator Controller.

6. DIGITAL SIMULATION RESULTS

6.1. Study Methodology

The superiority of the proposed WNN controller can be indicated by considering two different disturbances for two different operating conditions, and the studied power system responses are obtained. A comparative study between the proposed WNN static var compensator controller and the conventional proportional plus integral PI controller are performed and the results are discussed.

6.1.1 Application of three-phase short circuit fault

Figures 3 and **4** depicts the studied system response, with the proposed WNN controller and conventional PI controller when a three-phase to ground short circuit fault is considered at the generator terminal for 100 m. sec. The damping effect of the proposed WNN static var compensator controller over the conventional PI static var compensator controller is evident. The proposed WNN controller has a very fast response, with less overshoot and undershoot.

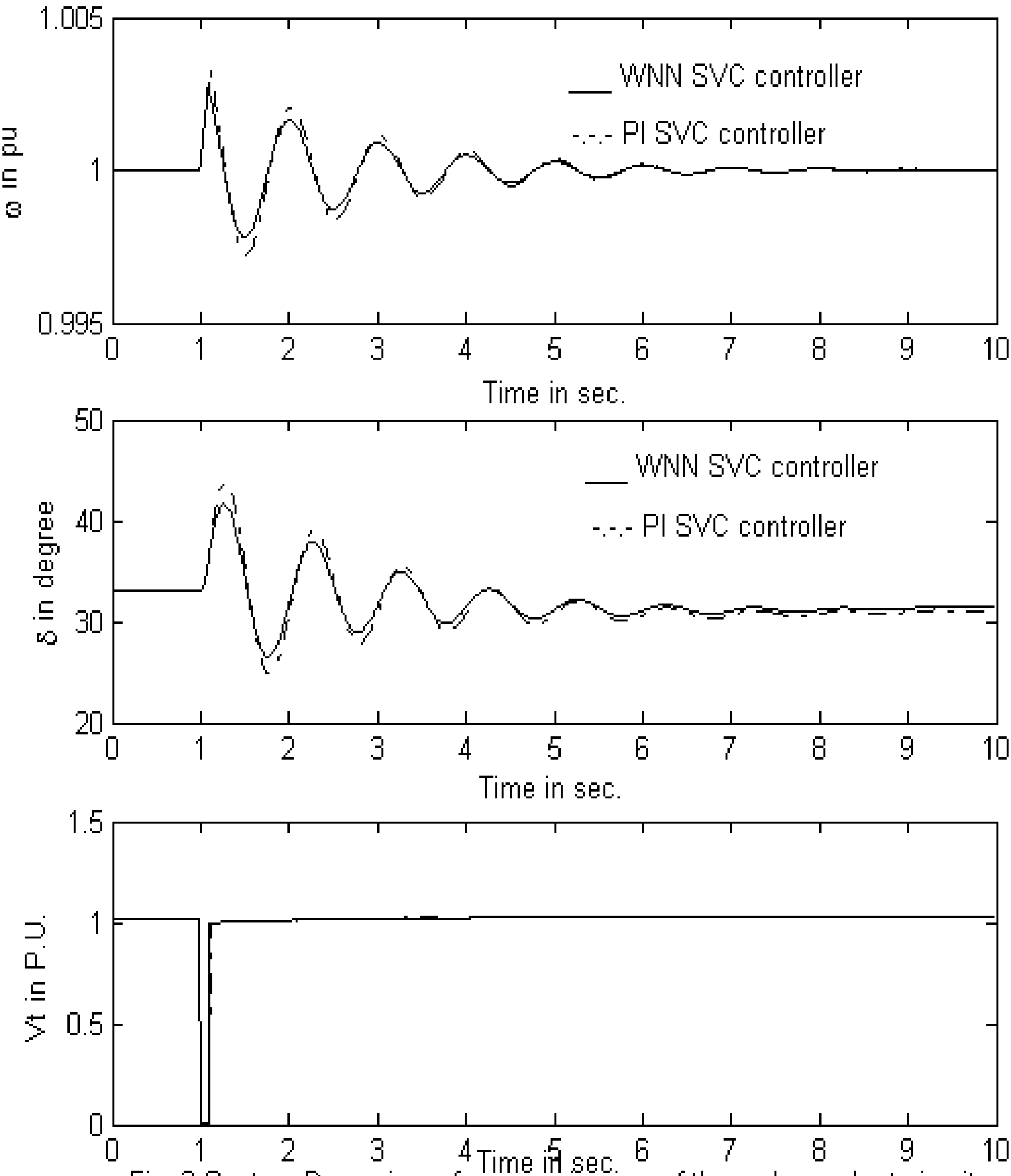

Fig. 3 System Dynamic performance in case of three phase short circuit fault with the proposed WNN SVC controller and PI SVC controller

p= 1.0 p.u Q=0.05 p.u

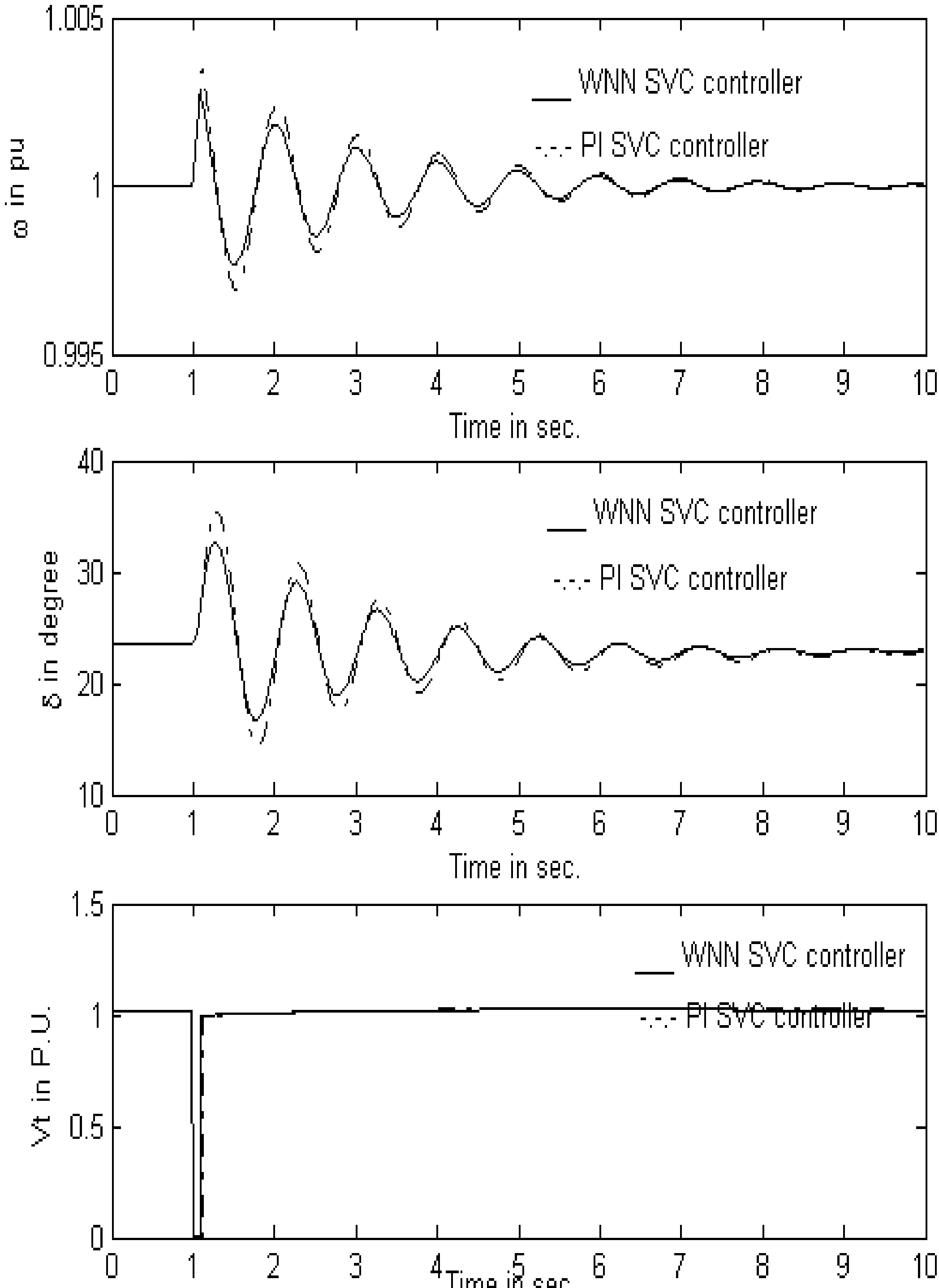

Fig. 4 System Dynamic performance in case of three phase short circuit fault with the proposed WNN SVC controller and PI SVC controller

p= 1.0 p.u Q=0.5 p.u

6.1.2 Application of Input mechanical power disturbance

Figures 5 and **6** show the studied system response when the generator is subjected to input mechanical power disturbance with SVC based WNN controller and SVC based PI controller. The damping effect of the SVC based WNN controller over the conventional PI controller is obtained. The proposed SVC based WNN controller has a very fast response with a very good damping adding to less overshoot and undershoot with better control quality.

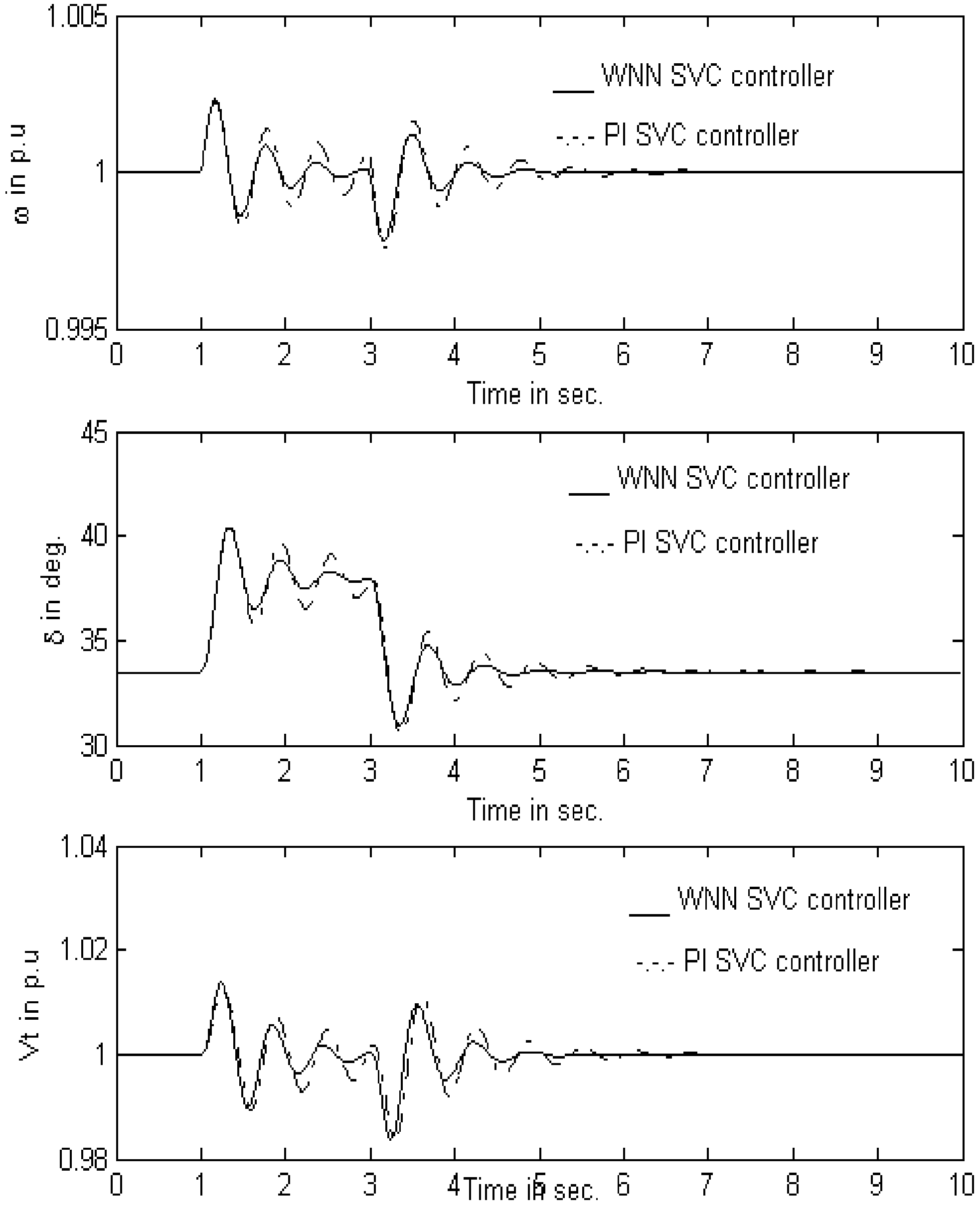

Fig. 5 System Dynamic performance in case of torque step disturbance fault with the proposed WNN SVC controller and PI SVC controller
p= 1.0 p.u Q=0.05 p.u

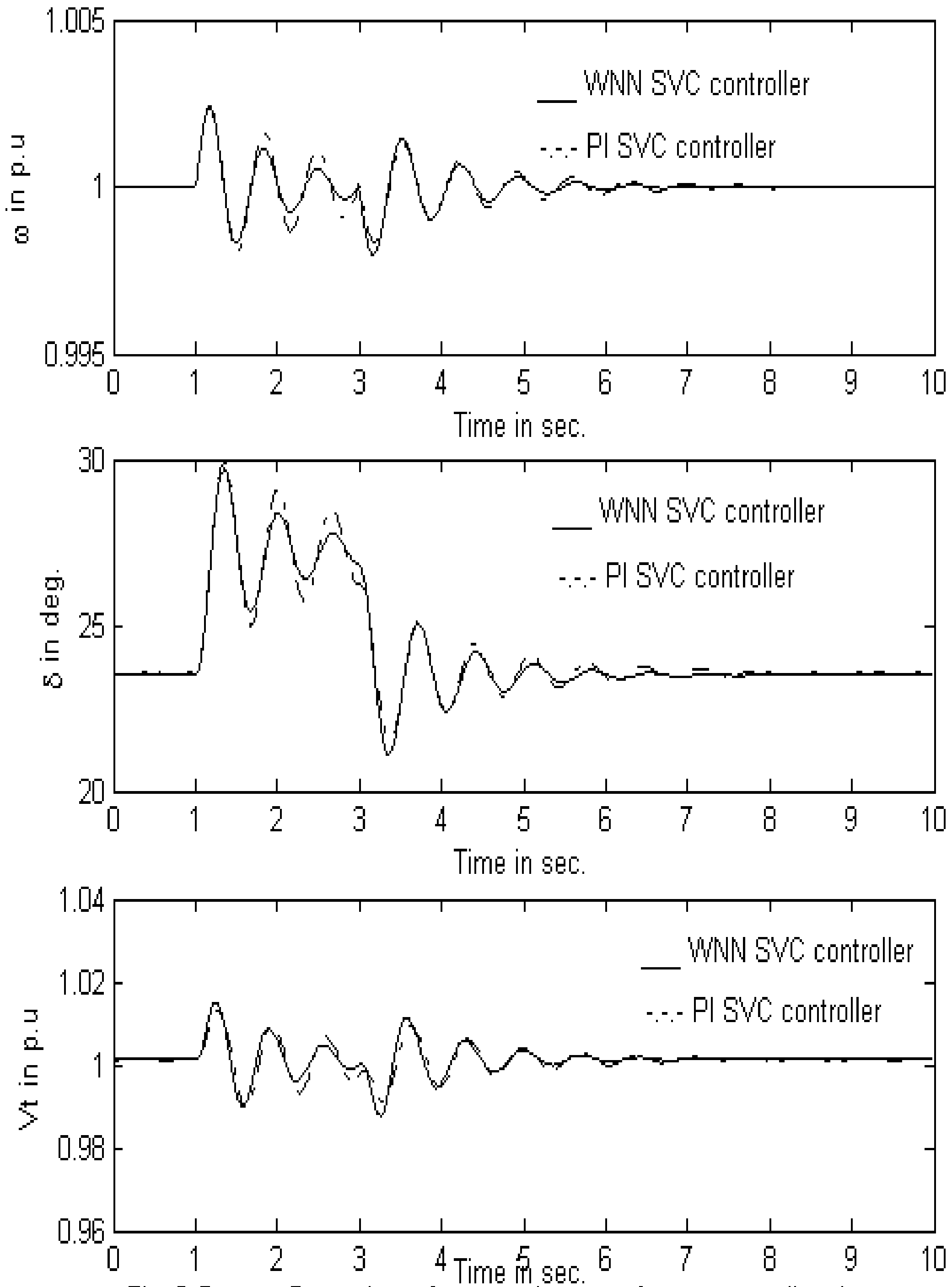

Fig. 6 System Dynamic performance in case of torque step disturbance fault with the proposed WNN SVC controller and PI SVC controller
p= 1.0 p.u Q=0.5 p.u

7. CONCLUSIONS

Wavelet neural network, WNN control technique has been used with SVC to improve the dynamic performance of the power system in case of abnormal conditions. The proposed control technique train the neural network on line and obtain a variable control parameters based on time simulation of the studied power system. The proposed WNN controller has established to provide a very fast response and better control quality.

To evaluate the effectiveness of the WNN SVC controller two different disturbances was considered with different operating conditions. The time simulation results prove the superiority of the WNN controller over the PI controller with very fast response and very good damping.

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محكمات الخلايا العصبية الموجية للتحكم في معوضات القدرة الغير فعالة الإستاتيكية

يقدم البحث تطبيق محكمات الخلايا العصبية الموجية للتحكم في معوضات القدرة الغير فعالة لضبط واتزان الجهد وتحسين أتزان نظم القوى الكهربية في ظروف التشغيل العادية أو أثناء وبعد حدوث أضطرابات. يوظف المحكم المقترح الخلايا العصبية الموجية للتحكم في كمية القدرة الغير فعالة المسحوبة من الشبكة أو التي يجب تزويد الشبكة بها. المحكم المقترح يوظف دالة غير خطية من الخلايا العصبية الموجية التي تستطيع تغيير بارامتراتها طبقا للأداء الديناميكي للشبكة. في هذا البحث استخدمت المعادلات اللاخطية التفاضلية والجبرية في نمذجة النظام المقترح للدراسة وتمت محاكاته باستخدام برنامج الماتلاب مع المعادلات المكتوبة له. وقد أثبتت النتائج تفوق المحكم المقترح على التقليدي من حيث الكفاءة وسرعة الاستجابة وإخماد الاهتزازات سريعا.